IMPROVING EMERGENCY DEPARTMENT THROUGHPUT BY ADOPTION OF AN ADMISSIONS PREDICTOR TOOL AT TRIAGE

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ABSTRACT

Benjamin Ovitt Linthicum: Improving Emergency Department Throughput by Adoption of an Admissions Predictor Tool at Triage
(Under the direction of Debbie Travers)

Emergency departments are increasingly busier and busier. An area of concern for many hospitals is how to deal with the resulting overcrowding and related throughput problems. This is because delayed throughput is seen as a measure of quality due to its association with negative patient outcomes.

In this quality improvement project I sought to use an admissions predictor tool at triage to improve emergency department throughput by changing the process by which patients are identified and then processed for admissions. A new process was put into place where a patient who was predicted highly likely for admission by the predictor tool would have a bed requested for them immediately after triage but prior to further emergency department evaluation. This would allow for parallel processing of emergency department evaluation during the inpatient bed assignment process.

A second goal for the project was to add to the collective evidence regarding the use of an admission predictor tool. This includes the practicality of its use as well as potential ways in which the tool could be improved upon or otherwise used beyond the early bed request process.

I found the admissions process to be much more complex than initially anticipated and due to this complexity only one patient out of 281 patients screened underwent the new early bed request process. I found that in order to successfully use the new process, patients not only need to be identified for admission but their admission service and level of care also need to be

identified. I found areas for improvement, of the admission predictor tool, namely the inclusion of comorbidities.

I was able to find a new use for the predictor tool. By calculating an admissions probability on all patients in the emergency department, not already identified for admission, the tool was used to predict bed needs for the whole department at one time. This aggregate prediction tool can be useful in planning hospital operations to meet the bed needs of patients' hours sooner than current methods.

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LIST OF ABBREVIATIONS

APT	Admissions predictor tool
BeRT	Bed request after triage
CC	Chief complaint
CICU	Cardiac intensive care unit
CMI	Case mix index
CMS	Center for Medicare and Medicaid services
DNP	Doctor of Nursing Practice
DVT	Deep vein thrombosis
ED	Emergency Department
EDWIN	Early warning system for overcrowding in the emergency department
FAM	Family medicine service
FIFO	First-in-first-out
EHR	Electronic health record
ESI	Emergency Severity Index
ICU	Intensive care unit
IHI	Institute for Healthcare Improvement
LVAD	Left ventricular assistive device
MAO	Medical admissions officer
MDA	Geriatrics medicine service
MDB	Nephrology medicine service
MDC	Cardiology medicine service
MDD	Heart failure medicine service
MDE	Oncology medicine service

MDH	Hospitalist medicine service
MDI	Intensive care medicine service
MDU	General medicine service
MDW	General medicine service
MED	Observation medicine service
NEDOCS	National emergency department overcrowding score
PDSA	Plan-do-study-act
PLC	Patient logistics center
SRE	Head and neck surgery service
SRG	Gastrointestinal surgery service
SRH	Acute and trauma surgery service
SRS	Cardiac Surgery Service
STOR	Statistics and Operations Research
UNC	University of North Carolina
UNCH	University of North Carolina Hospitals

CHAPTER 1: INTRODUCTION

Problem Statement

Every year Emergency Departments (EDs) are busier and busier. The most recent national data available are from 2014, a year in which there were 141.4 million ED visits in the United States, which was up from 136.3 million from 2011 (Centers for Diesase Control and Prevention, 2014; CDC&P, n.d.). This often results in overcrowding that has been linked to numerous negative patient outcomes to include delayed interventions, poor satisfaction, and most importantly increased mortality (Johnson & Winkelman, 2011).

How to deal with this ever-increasing volume is a common challenge facing EDs nationwide. Emergency departments strive to decrease the time it takes to process patients, or in other words, improve throughput. Throughput of patients is a marker of efficiency and is used as a measure of quality of care coordination and patient engagement by the Centers for Medicaid and Medicare Services (Centers for Medicaid and Medicare Services, 2014). This makes improving throughput important not just an internal and patient centered goal, but also one associated with regulation and reimbursement. Currently, The Joint Commission does not require measurement or reporting of specific ED throughput metrics, but does make certain recommendations that patients wait no more than 4 hours in the ED after the decision to admit them has been made (Joint Commission, 2012, 2013). This is commonly known as boarding time. This is a wasteful time when patients occupy space in the ED without receiving services. This occupied space prevents other ED patients from receiving services. It is well established that boarding of admitted patients in the ED negatively impacts ED operations (Fogarty, Saunders, & Cummins, 2014).

Exactly how to improve throughput remains a source of scholarly inquiry. Numerous strategies have been attempted to improve throughput. They include operational changes such as immediate bedding of patients thereby bypassing triage or conversely placing a provider in triage, as well as interventions that focus on technology to improve registration and communication (Wiler et al., 2010). There have also been attempts to improve flow by adding a nurse specifically to manage the flow of the ED (Murphy, Barth, Carlton, Gleason, & Cannon, 2014). These interventions have generally been successful at least to some degree, but tend to look more generally at all patients in the ED or flow within the ED. They do not focus on admitted patients. This project was designed specifically to focus on improving throughput of **admitted** patients.

Purpose of Project

The purpose of this Doctor of Nursing Practice (DNP) scholarly project was to improve the throughput of the ED by utilizing a tool to predict which patients would be admitted based on information collected at triage in order to start the inpatient bed request and admission team assignment as soon as possible. Currently, standard practice is the admitting process takes place after patients have been evaluated by an ED provider, had diagnostics completed and have been determined by that provider to require admission. While sometimes this is a quick process, most often it can take hours. For the purposes of this project, it was assumed that using parallel processes (ED evaluation, inpatient bed and admission team assignment) could expedite patients' throughput in the emergency department. I sought to decrease non-value added time of patients occupying an ED bed without receiving service, which was hypothesized to be a sizable contributor to the problem of slow throughput. This wasted occupied bed space is of paramount importance to the larger goal of this project which was to improve throughput not just for the patients who receive early bed request, but for all patients in the ED (Krall, Guardiola, & Richman, 2016; Wiler, Bolandifar, Griffey, Poirier, & Olsen, 2013).

For this DNP project, a locally developed predictor tool was utilized using data specific to the population of the implementation site within the ED at the University of North Carolina Hospitals. The tool uses data specific to this site. The goal of this project was to improve ED throughput on the local level and add to the collective evidence about the practicality and benefit of using such a tool and an early bed request process named Bed Request after Triage (BeRT).

Significance to Healthcare

If successful in improving throughput at the project site, this tool and process could have served as a model for other EDs to follow. This strategy could provide an additional tool in the arsenal of ED operators interested in improving throughput.

Review of Literature

In order to inform this project and place it within the greater context of ED throughput work a literature review was conducted.

Search Strategy

PubMed was searched without limitations using the terms (flow OR throughput) AND (admission) AND (ED OR "emergency department") with results of 538. After sorting these results by relevance and then screening the abstracts, I found 15 articles clearly related to this problem and more specifically examples of several attempts to implement admissions prediction tools at triage in order to mitigate the problem (Bradman, Borland, & Pascoe, 2014; Crilly et al., 2015; Peck, Benneyan, Nightingale, & Gaehde, 2012; Peck et al., 2013; Sun, Heng, Tay, & Seow, 2011). Most articles were excluded because they were not specific to EDs, throughput, or overcrowding. The articles were included if they were published in English and address either predicting admission or alternative strategies for dealing with boarding times. Articles were not excluded based on age but all were published within the past 10 years. Similarly, size of the institution was not considered with regards to exclusion or inclusion of articles. Those 15 found to be most applicable to this project are included in this review of literature and are subdivided into the themes. Appendix 1 is a PRISMA flow diagram describing this process.

Themes from Review of Literature

Several themes applicable to this particular project begin to develop as the literate surrounding the subject was examined. Themes included: the relationship between boarding of admitted patients in the ED and crowding, the development of some sort of admissions predictor, the way in which these predictors where implemented, and issues surrounding poor ED throughput and impact of boarding patients.

Theme 1: Admissions Predictor Tools or Methods

In the literature there appears to be very limited attempts to develop a way of predicting admission outside the traditional method of ED provider opinion after diagnostic evaluation and testing. Perhaps this is because use of such a tool is only one way of attempting to reduce overcrowding. Probably more likely is that developing such a tool is a very complicated undertaking.

The simplest version of predicting admission early in the ED visit is utilizing the opinion of those involved in the ED visit. This includes the opinions of providers and nurses. Typically, the decision to admit a patient is done by the provider after the patient is examined and diagnostic tests are completed. Simply asking providers of patient care to flag patients for admission earlier in the visit is a low technology way of allowing for parallel processing of ED evaluation and bed request to occur.

Several studies have looked at using ED personnel to predict admission at triage (Bradman et al., 2014; Stover-Baker, Stahlman, & Pollack, 2012; Vaghasiya, Murphy, O'Flynn, & Shetty, 2014). Nurses were found to predict admission with relatively good accuracy and in at least one case outperform an admission predictor tool (Bradman et al., 2014). Still, there is concern for over-predicting admission when utilizing the strategy of ED provider opinion. Over prediction, or having too many false positives, is a potential problem of nurse opinion being used to predict admissions (Stover-Baker et al., 2012). Likely when asked, nurses and others may try to predict admission more often than not in an effort to try to please the investigator. There may be some implicit bias in just asking the question, "Do you think this person will be admitted?" If the case appears borderline to the nurse being asked the question, they may err on the side of saying, "yes." The nurse may be motivated to capture all admissions and be willing to over predict in order to do this. The nurse may prefer to over predict than under predict in an effort to appear more accurate as well in order to capture all potential patients. To the individual nurse this makes sense, but from a systems standpoint the over prediction may lead to a breakdown in usefulness of predicting admissions. Too many false bed requests would simply create a further throughput issue by adding additional strain on the admissions process.

One may ask if nurses in triage are the best-qualified group to predict admissions given that providers typically are the personnel within the ED who regularly make the admissions decision. In fact, physicians do perform slightly better given the limited literature in this area (Vaghasiya et al., 2014). Registrars (Attending Physicians) and Consultants (Resident Physicians) do slightly outperform nurses in accurately predicting admissions in this order with information only available in triage. However, the difference does not appear to be significant enough to place a physician in triage for this purpose alone. Currently, in most EDs, triage is an area that nurses are primarily responsible for. If utilizing ED personnel opinion only, then nurses would be a satisfactory method of doing so and this would not require a redistribution of personnel resources. With regards to process change it is not clear if the health system would be willing to change their processes based on triage nurse opinion alone, even if it is validated. For this reason, a validated standardized tool may provide more consistency to allow for such a process change.

Another way of predicting admission is to look simply at demographic data (Sun et al., 2011). This type of tool takes into account information already known about the patient at arrival, particularly if the health system and medical record system includes complete patient information. This type of information would include age and ethnicity, and perhaps some information about medical history. It would not include information related to the ED visit itself. It relies on information already known about the patient and does not gather any additional information at the time of triage. For instance, this tool type does not differentiate between a patient who is presenting to the ED for a stubbed toe or shortness of breath. There are several advantages to this type of tool. From an ease-of-use perspective, it does not require the gathering of much information. From an operational perspective, it would allow prediction of admission as early as possible. As soon as the person registers in the ED a prediction could be made. It would not require any information gathering from triage. The concern with this type of tool is that it may be too general and likely not intuitive for clinicians to use.

For a clinician, the expected way of predicting admission would include more than demographic data alone. Such a prediction would include clinical data such as chief complaint, laboratory values, or vital signs. Clinicians would expect this integration of clinical data to make the prediction more accurate because this is the type of information used to predict admission in the standard process of deciding admission. A study of admissions predictor data conducted at the same site of this project attempted to identify predictors of admission for elderly patients, and found that certain chief complaints, Emergency Severity Index (ESI) level, and specific vital signs were predictive of admission (LaMantia et al., 2010). ESI level is a 5 level system for expressing patient acuity with level 1 requiring immediate resuscitation through level 5 which are stable patients. Both demographic and clinical data were found to be helpful, as most clinicians would expect. LaMantia and colleagues (2010) also utilized logistic regression to identify the predictors much in the same way the tool for this project's admission tool was developed. At least one other article has shown the advantage of using similar statistical models to develop predictor tools over expert opinion (Peck et al., 2012).

Ultimately, whatever the prediction method utilized for this type of project, it must be accurate yet not over predict admissions. The tool used for this particular project has been tested in a computer simulation and was shown to improve throughput (Riederer, 2016). The tool is called the Admissions Predictor Tool (APT) and predicts admission utilizing data available at the completion of triage, including a mix of demographic data such as age, but also is tailored to include information about the visit itself such as chief complaint (Travers et al., 2016). Specifically, the APT uses age, chief complaint, and ESI level to calculate a probability of admission based on past patient presentations with these same variables. The APT was developed using all visits (N=65,503) at a tertiary care medical center ED during a one year period by a multidisciplinary team consisting of professionals with expertise in operations, medicine, nursing, administration, statistics, and informatics. At the study site, the APT with a probability level of 95% can accurately predict admission for 14 patients every day while only inaccurately predicting less than 1 admission every two days. At a 90% probability the tool predicts 19 admissions per day from triage with only 1 false prediction. The tool has recently undergone further pilot testing (Ring, 2018).

Theme 2: Issues Surrounding Emergency Department Throughput and the Impact of Boarding Patients

There are numerous issues surrounding throughput in the ED. The ED is a place of finite resources with a nearly limitless potential for input of patients. It has a finite capability not only to process patients but also to output those patients either by discharge or admission. This project was specifically designed to impact ED throughput by more efficient use of the resource of **time**. There is a large amount of literature regarding ED throughput. A portion of it is reviewed here as it relates to this project.

With regards to how poor throughput and its surrogate ED overcrowding relates to patient care, it is of paramount importance to understand how crowding impacts patient outcomes. One thorough review of the literature demonstrates quite well that ED overcrowding impacts several patient outcomes including patient satisfaction and more importantly mortality (Johnson & Winkelman, 2011). This review examined 23 studies that looked at patient outcomes and ED overcrowding. The authors grouped these outcomes into three themes. These are delayed interventions, patient satisfaction, and mortality. Delays in interventions associated with increased overcrowding included pain control, antibiotic administration, EKGs, and percutaneous cardiac interventions. These delayed interventions cause, poor outcomes, real suffering, and decreased quality of care. Patient satisfaction decreases with ED overcrowding based on this review. Most importantly, ED overcrowding was found to be associated with increased patient mortality. Much of the overcrowding from the studies in this review was associated with boarding of admitted patients. This means that improving throughput will have real impact on patients.

This project addressed the throughput of admitted patients and does not specifically intervene to address the throughput of discharged patients. Nationally, it is known that academic EDs tend to have more difficulty processing admitted patients (Horwitz, Green, Fau-Bradley, & Bradley, 2010). This is likely because EDs have greater control of the discharging of patients, while admitting patients require more coordination with other hospital departments and processes. Larger hospitals like academic centers have a greater number of departments and teams within those departments. Within the UNC system this can be clearly demonstrated. UNC Rex, a community hospital in the system, has just one medicine team that admits patients to inpatient floor beds, while UNCH proper has 13. Still, those admissions policies and processes can be changed to decrease the length of stay for admitted patients (Kang, Nembhard, Rafferty, & DeFlitch, 2014).

Although my project focused on admitted patients, it was thought that it might still impact the length of stay of discharged patients. There is a growing body of evidence that demonstrates when admitted patients are boarded the length of stay for discharged patients also increases (Fogarty, Saunders, & Cummins, 2014; Kang et al., 2014). The reasoning is simple, if there are admitted patients boarding in the ED this ties up ED resources caring for these patients and it does not allow the ED to process other patients. This project had a real potential to impact the throughput of not only the admitted patients it seeks to process more efficiently, but discharged patients as well.

<u>Theme 3: Implementation of an Admissions Predictor Tool</u>

Implementation of a practice change is a key component of DNP scholarly work. It is this translation and implementation science work that is the value of DNP knowledge (Burson, 2017). Wiler et al. (2010) looked at projects to help EDs manage overcrowding. These included immediate bedding of patients/quick registration, advanced triage protocols, provider in triage, "fast track" service lines, and improved communication methods. However, the science of implementation of these types of changes is not often reported in the literature as it relates to ED overcrowding. Still, within the health sector there are numerous models for implementers and change agents to use, such as the Institute for Healthcare Improvement (IHI) Model for Improvement (IHI, n.d.).

As reviewed in theme 1, there have been several attempts in the literature to develop ways of predicting admission. However, it appears there has been much less published on the implementation, adoption, and subsequent impact of those tools. There is evidence that implementing changes to admission processes can impact length of stay (Kang et al., 2014), but this project was specifically looking at early identification of admitted patients in addition to process changes.

Process changes, combined with the use of the predictor tool would seem to improve throughput but the limited information reported in the available literature is not clear. The two examples of the implementation of similar tools suggest that the tools may be helpful but data collection seems to be one challenging issue of evaluating implementation (Peck et al., 2013). Similar to the issue of data collection is that given the multitude of factors that impact patient length of stay it is difficult to specifically attribute improvements in length of stay to the predictor tool alone (Crilly et al., 2015).

Given the weakness of the information regarding how to implement and evaluate an admissions predictor tool, for the purposes of this project, particular attention was paid to this theme in planning implementation. Although this project was about the implementation of a tool, it is a novel tool, different from previous attempts to predict admission. As a result, a large portion of this project was about discovery of the best ways to utilize this particular tool.

Summary of Review of Literature

There is ample evidence that ED length of stay for admitted patients can be impacted by thoughtful interventions and that the impact of these boarding patients will benefit other ED patients in terms of not only length of stay, but potentially also important patient outcomes such as mortality. There have been attempts to predict admission at triage using various strategies. The tool used in this project is novel but similar to other tools. However, this tool was developed specifically at the site of implementation and thereby it was thought increasing its chance of successful adoption. There is limited information on how to implement and measure the impact of this type of admission predictor tool and this project will expand the scholastic knowledge regarding such future attempts at adoption. Overall, the literature on the subject was helpful in considering the ways in which to develop this project and consider its impact.

Theoretical Framework

With this project I aimed to decrease boarding time thereby improving ED efficiency, but I predicted this change would also improve flow for all patients, not just those who have been admitted. I utilized portions of Queuing Theory to guide this project. Queuing theory is the study of waiting in lines. It is the mathematical way of expressing this wait. This is a strategy that is supported in the literature and based on Queuing Theory principles (Kang, Nembhard, Rafferty, & DeFlitch, 2014).

Essential I of the Essentials of Doctoral Education for Advanced Nursing Practice focus on the scientific underpinnings of practice (American Association of Colleges of Nursing, 2006). This means that DNP students and graduates should be able to pull not only from nursing science, but also from other scientific disciplines as well. The DNP must not only be able to understand nursing knowledge but also incorporate knowledge from other disciplines in order to positively impact patient care or patient care delivery systems. In the case of this DNP project, Queuing Theory comes from the sciences of Operations Research and Statistics. The Admission Predictor Tool used in this project was developed with the aid of faculty and graduate students from the University of North Carolina at Chapel Hill Department of Statistics and Operations Research (STOR). This project truly pulled from multiple scientific traditions, including systems engineering, operations research, and business/healthcare management.

Queuing Theory has been used in EDs but also other areas of healthcare with success. It has been used in areas to improve efficiency as varied as pre-anesthesia areas (Zonderland, Boer, Boucherie, de Roode, & van Kleef, 2009) and inpatient pharmacies (Bahadori, Mohammadnejhad, Ravangard, & Teymourzadeh, 2014). The project site, UNC ED, has been simulated using queuing simulation models in an attempt to better anticipate overcrowding (Ahalt, Argon, Ziya, Strickler, & Mehrotra, 2016). Even though it is not familiar to nursing, its use has the propensity to greatly impact nursing and the systems in which nurses operate.

The application of a non-nursing theory to a DNP project is not novel but was an exciting prospect. It certainly is in the spirit of Essential I of the Essentials of Doctoral Education for Advanced Nursing Practice. This project, although justifiably a DNP project in that it impacts delivery of patient care, could just as easily have been the project of a systems engineer, business school graduate, or physician. It sought to impact a system not just an individual patient, yet the ultimate goal was improved patient care. Improving care and care environments using available science is at the heart of nursing and the goal of the DNP. Emergency department work by its very nature is interdisciplinary. In the ED nurses, nurses aids, ED physicians, consultants, radiology personnel, etc. all contribute to the care of one patient.

Queuing Theory serves a purpose in both defining the problem and guiding the intervention of this project. In the case of this DNP project the two are intimately related. Defining the reasons for long waits in the ED and how to address the causes of those waits are both described well in the terms of Queuing Theory.

Queuing Theory deals with the systems and processes of a queue. It was originally developed more than 100 years ago in order to help explain telephone switchboard operations at a time when one had to wait for a telephone line when making a call (Bhat, 2010). This theory attempts to describe and predict the multifaceted issues surrounding queues. It is largely a mathematical theory, however this theory has numerous applications from transmission of data over fiber optic cables, to vehicular traffic patterns, to waiting in line at an airline counter (Bhat, 2010). Essentially, wherever there is a process where things or people have to take turns, Queuing Theory can be utilized. An ED with its multiple queues is perfect for application of the theory.

The theory can get very complicated but at its simplest core it is about how many people are waiting in a queue. Mathematically, the number of people waiting is equal to those who arrive minus those who have been processed over a given time. This is known as Little's Law (Bhat, 2010). It is a simple concept but important to a deeper understanding of the theory at work. What this mathematical concept means is that in a given system you have to either decrease the number of arrivals or improve the processing capacity in order to avoid having people wait. The theory becomes more complicated as a more variables are introduced and there are many other concepts within this theory. For instance, a common issue addressed within the theory is that one has to decide the most efficient way to process people. Processing people in order of arrival, known as first in first out (FIFO), is one method, however in some situations it is more efficient to bundle patients together and processes them simultaneously (Bhat, 2010).

The most basic way that Queuing Theory guided this DNP project is by use of Little's Law. There are only two essential variables that impact the number of patients waiting: 1) the number of people coming into the system and 2) the number of people leaving the system. Thus, ED crowding interventions address either patients arriving at the ED or being dispositioned from the ED. Little's Law addresses well the problem of long ED waits and boarding of admitted patients. The intervention of early identification of admitted patients is addressing specifically the number of people leaving the system. The hypothesis is that this intervention will result in more rapid patient extrication from the system resulting in less people waiting at any given time. The limitation of Little's Law is that it does not describe how to have people exit the system quicker but it leaves the user of the Law free to decide upon the best option for the given situation.

Another way that Queuing Theory can be described is by use of the notation:

A/B/s: (d/e)

A is the arrival pattern, **B** is the service-time distribution, **s** is the number of servers, **d** is the maximum number who can be contained in the system at one time, and e is the queuing discipline (Lee, 1966). **E** or the queuing discipline is of particular interest to my project's intervention. This is where, in Queuing Theory, one must decide how you will process patients. In our daily lives we are used to first in first out (FIFO) lines. This is a how most queues operate be it lines at the grocery store or a drive through window. In these cases, people are processed in the order that they arrive. Queuing Theory states that this is not always the most efficient way to process patients. Rather, each system is different in terms of goals and processes, so the best way for one system to operate may not be the best way for another.

In the ED, there is a degree of FIFO processing but for the most part EDs consider acuity of patients when deciding on whom to process next. Sicker patients wait less time than less sick patients, e.g., a person having a heart attack waits less in the queue than a person with a sprained ankle. Only if two patients, both with sprained ankles, are waiting does FIFO processing occur. However, for the admissions process the queuing discipline is different. Here patients are processed in a first-in first-out (FIFO) queue. This means that patients identified for admission first are processed in order of identification. Given this FIFO process, early prediction of admission could result in less queuing time for admitted patients because their admissions queuing time will be built into their ED service time, as opposed to occurring one after the other. Understanding what **e** represents in the queuing model allows for an understanding of how impacting it will impact patient waiting times and throughput.

Applying Queuing Theory, bottlenecks such as admission processes are viewed as large contributors to delays of a system. These are places in the system where there are a limited number of servers (**s**) or limited number of patients who can be served at one time (**d**). Queuing Theory has been applied in studies that identify those bottlenecks and address them within the ED (Abujudeh, Vuong, & Baker, 2005). In development of the Admission Predictor Tool, the team from STOR developed a model of the ED in order to predict admissions and test the impact of early admissions identification (Riederer, 2016). This type modeling is common in statistics and operations research, and has been applied successfully in order to improve overall Emergency Department flow (Alavi-Moghaddam et al., 2012; Wiler, Bolandifar, Griffey, Poirier, & Olsen, 2013). This modeling allows departments to test different scenarios such as adding different staff or changing processes in order to improve flow prior to actual implementation. Multiple scenarios can be tested much quicker and without impacting patients or staff prior to any institutional change. They are a cost effective way of trialing changes to systems.

The model developed by the STOR team members predicted that if patients were identified for admission early and thereby processed quicker by the admissions team, then all patients in the ED would move through the system quicker (Riederer, 2016). Viewing this in the context of Little's Law explains this phenomenon: increasing departures from the system results in decreased waiting. This is also consistent with the A/B/s: (d/e) description of Queuing Theory, whereby d is the number of people who can be contained in the system. If it is constant, as it is the ED at any given point, then decreasing this number can improve efficiency of they system. Interestingly, in one study, a Queuing Theory based model was used to demonstrate that an ED would have to literally double its capacity to eliminate waits completely (Haghighinejad et al., 2016).

Queuing Theory anticipates that by impacting the queuing discipline this project will decrease wait times. This is what the Riederer (2016) model has done, but the real world is much more complicated.

It would be virtually inconceivable to develop a project like this DNP project without considering Queuing Theory. Once one starts to consider waiting times, processing of patients, or improving efficiency one is using Queuing Theory consciously or unconsciously. Quite literally, any intervention that could be attempted to improve ED throughput would be addressed in the A/B/s: (d/e) description. If a project sought to make ED staff work harder then it would address **B** (service-time distribution). If a project sought to decrease the number of people who utilize the ED then it would address **A** (arrival pattern).

Beyond order, utilizing Queuing Theory makes the project easier to communicate with other disciplines. The theory is used in Operations Research but also familiar to those who work in areas of business and management. Framing this project in a theory that has uses in multiple disciplines lends credibility to those outside the profession of nursing and provides a common language when communicating concepts to others.

CHAPTER 2: METHODS

Design

This project was designed as a quality improvement initiative. The purpose of this Doctor of Nursing Practice (DNP) scholarly project was to improve the throughput of the ED by utilizing a tool to predict which patients would be admitted in order to start the inpatient bed request and admission team assignment as soon as possible as well as lay the groundwork for future quality improvement changes with similar methods on a larger scale. This project focused on a limited implementation of a novel way to identify patients for admission and a process to expedite their bed assignment to the hospital. This new parallel processing of ED evaluation and inpatient bed assignment/inpatient team assignment would occur for patients identified by the APT. The project was to trial the feasibility of this method of admission. Similar quality improvement projects within this organization have been trialed on a limited basis for feasibility in much the same manner and have led to wholesale adoption once the trial has proven successful. An example of this is a provider in triage model of patient care. This project utilized data collection methods similar to other quality improvement projects with not necessarily a goal of statistical significance but rather a goal of seeing operational metric improvement.

Setting and Resources

The setting of this project was the ED of the University of North Carolina Hospitals (UNCH) located in Chapel Hill, North Carolina. It is a large referral center for the state of North Carolina with a high patient acuity having an admission rate of nearly 30% for its approximately 70,000 patient visits per year (UNC School of Medicine, 2015).

In addition to a high rate of admissions the setting of this project, UNCH struggles with excessive boarding times. Based on available Medicare (2017) data the facility has a longer boarding time compared to local hospitals, including a nearby academic center that has a comparable patient population, as well as compared to national averages. Appendix 2 includes details from Medicare; UNCH has a median boarding time of 237 minutes, while the nearby academic ED's is 148 minutes and the national average is 131 minutes.

The resources required for this project included the bed request team, the admissions teams, and myself (a DNP student & nurse practitioner who practices in the UNCH ED). The bed request team consists of the house supervisors and Bed Control. These individuals work in coordination with a medical admissions officer (MAO) who is a liaison between the ED and the medicine admitting teams that consist of physicians and advanced practice providers.

The MAO, who is a nurse, receives information about an intended admission from either an ED provider or another provider such as a community physician and coordinates with the medical teams to assign a particular team to the patient. The MAO then places a verbal order for the patient to be admitted to an inpatient bed or the admission team evaluates the patient and then places the order. This then signals the bed request team to find the patient an appropriate bed. The location of the bed at UNCH is regionalized to a particular part of the hospital based on the particular inpatient team that will be caring for the patient. Once assigned a bed and after having been seen by the admission team, the patient is transported to an inpatient unit.

Study Population

The sample involved in this project was a convenience sample of patients who present to the ED with medical complaints during the project enrollment period. These were distinct patient complaints from surgical patients. While there can be some overlap of these two groups, typical examples of medical patient complaints include chest pain, fever, and shortness of breath.

They did not include typical surgical patient problems such as trauma or injuries. The medical teams at UNCH only covers adult patient so only adults (19 years old or greater) were included. Also not included in this project were patients who likely will need psychiatric evaluation such as those presenting with chief complaints of suicidal ideation or hallucinations. Admission of this population has its own unique challenges and the APT was not developed to address prediction of these patients.

Procedures

This project was formulated using a two-step process. The first step was to identify those patients who the Admission Predictor Tool suggests a high probability of admission. The second step was to expedite the actual admissions process by initiating a bed request after triage (BeRT).

<u>Step 1: Predict Admissions</u>

I physically sat with the MAO in the ED one or two days per week over the two-month study period. The predictor tool was run using a laptop computer on all adult patients who present to the ED with medical complaint during this time frame. This was done using only data located within the EHR and did not require any additional information or interaction with the patient. The tool utilized only data routinely collected in the triage and registration process. The patients were initially considered predicted for admission if the tool indicated a 90% or greater probability of admission.

<u>Step 2: Initiating the Admissions Process</u>

Once a patient was identified as having a high probability of admission, the plan was to work with the MAO to initiate the admissions process, which we called Bed Request after Triage (BeRT). Early identification of a high likelihood of admission without early initiating of this process would not likely positively improve patient flow. This initiation of admission required an order to start the bed-request-team's work in identifying a bed as well as identifying an inpatient team to care for the patient. This process required the knowledge of the MAO as the various teams have different guidelines for which patients they admit. Further, there are restrictions placed on residents regarding the number of patients they can admit during a given time period and the MAO helps to track this. Initially for this project we limited patient enrollment to two of the admissions teams, MDU (General Medicine) and MDA (Geriatrics Medicine). These two teams where chosen because Med U tends to have consistent attending coverage by hospitalists who understand the admission process well and MDA services the elderly, who were more likely to be admitted based on the APT.

Data Collection and Evaluation

<u>Step 1: Identifying Patients for Inclusion in Project</u>

I initially included patients in this study who had a 90% or greater probability of admission based on the APT. The admission probability was calculated by entering the patient's chief complaint, age, and ESI level into the APT web application on a laptop computer at the conclusion of triage. I collected data on all medical patients with an APT score of 70% or greater. These data were intended to be analyzed in order to inform potential future expansions of the APT and BeRT process.

<u>Step 2: Data Collection</u>

Data surrounding the admissions process and the impact on those quality metrics were of particular importance for this project. Routinely UNCH ED gathers data regarding door-to-admission time. These data are collected on all patients who present to the ED and are admitted. These data are seen as a metric of the quality of timeliness of care received at the facility. Door to admission time was collected on those who were identified as having a high probability of admission. The intent was to compare the patients who are identified by the APT and undergone the BeRT process to those who are not identified by the APT and processed through the ED by the standard process. See Appendix 3 for the data elements that were collected on all medicine patients with an APT threshold 70% or greater.

Step 3: Qualitative Data Collection

In addition to the time based data I also planned to gather impressions of those involved in the new process. I intended to collect qualitative data in the form of open-ended questions from the MAO, bed control, and admission team providers as well as ED providers involved in the care of the patients who underwent the BeRT process. This includes ED resident and attending physicians as well as MDA and MDU residents and attendings. This was to be collected after the trial period is over in order to gather general impressions of the process. Given that this project was a trial, the goal was to understand what went well and what could be improved upon. These questions could have been used to help further improve the BeRT process if it were fully adopted after this project was completed. See Appendix 4 for a list of the intended questions. A list of staff members, as listed above, involved in each patient who undergoes the BeRT process was to be maintained in order to identify those patients who can be surveyed after the trial period has ended. Completion of the survey was to be completely voluntary.

Step 4: Data Analysis

After the quantitative and qualitative data had been gathered it was to be analyzed to better understand the impact of the APT and BeRT.

The quantitative data were to be analyzed to see if there were patterns that arose from the trial period that may have improved or hindered the process. For instance, the process may have worked better on a particular day of the week or with a particular admission team. Certain chief complaints may have emerged as commonly identifying as having a high rate of admission but not to the 90% cut off yet still benefit from being included in a future implementation of this process.

The qualitative surveys were planned to be analyzed to look for themes that may have emerged. It may have been that the BeRT process was viewed favorably by one group but not another. Staff members may have had ideas for refinement. This qualitative data would be useful in improving the process and making a full-scale implementation successful.

PDSA Changes to Methods

In this project I applied a widely used healthcare quality improvement approach, the healthcare quality Plan-Do-Study-Act (PDSA) cycle (IHI, n.d). Each PDSA cycle includes intervention planning, implementation, and then evaluation. After being evaluated the intervention may be continued as initially envisioned or if there is a possible improvement identified then the change is made and another cycle starts.

When this project was originally planned it was thought that the best use of the APT would be to identify individual patients highly likely to be admitted, and then initiate an expedited admissions process using the Bed Request after Triage (BeRT) process. The successful implementation and evaluation of this process was conceived as a key part of the project and consistent with the goal of improving patient throughput in the ED. As a result, I conducted several iterative cycle changes to the project methods in order to seek improved implementation of the BeRT process.

The first change was the addition of a revised version of the APT. The initial APT planned for implementation was actually the second version of the APT or APT v.2. A third version of the APT or APT v.3 became available just as I started the implementation of my project. APT v.3 was similar to APT v.2 but was built from a larger bank of patients, and a larger chief complaint list that was identical to the one available in the EHR used by the study site. APT v.2 has 69 chief complaints and is based data from 64,326 patient visits over 1 year. APT v.3 has 385 chief complaints and is based data from 221,102 patient visits over 4 years. In this study I ran both versions of the APT on each patient, and collected data on study subjects if either version meet or exceed the threshold of 70% admission probability.

The second and third changes occurred simultaneously. After 2 weeks of patient enrolment, there were no patients who were successfully processed with the BeRT methods. I then made the decision to expand the inclusion criteria to include to all medicine services including Family Medicine, not just MDU and MDA. The other change I made was to lower the requirement for initiation of the BeRT process from a threshold of 90% to a threshold of 85% for either APT. This was intended to increase the potential number of patients who could undergo the process.

The final PDSA cycle was undertaken because of continued lack of patients for whom I was able to initiate the BeRT process. This was a major change in which I focused on using the APT on all current ED patients likely to be admitted, who had not yet been identified for admission. I computed an APT score for all patients with medical chief complaints currently in the waiting room or in the process of ED evaluation the, and their predictive scores were averaged to produce an aggregate prediction score of future admissions.   I developed a method to report out this aggregate prediction to the MAO, ED administrative staff, and ED attending providers. A hypothetical sample of this table is presented in appendix 5. My goal was to evaluate whether this aggregate prediction of likely admissions was feasible and helpful in predicting future inpatient bed needs. Appendix 6 includes questions asked of the MAO, ED administrative staff, and ED attending providers in order to evaluate its usefulness.

CHAPTER 3: RESULTS

Description of Patients Screened

Between October 11, 2017 and December 15, 2017 a total 281 patients met inclusion criteria and were screened using both the APT v.2 and APT v.3. Table 1 and table 2 show the distribution of those predictions for APT v.2 and APT v.3, respectively.

Table 1: Distribution of APT v.2 screening predictions

APT Prediction	Number Predicted (N=281) and Percent
0-19%	70 (25%)
20-39%	80 (29%)
40-59%	63 (22%)
60-69%	18 (6%)
≥70%	50 (18%) *41 also predicted with V.3*

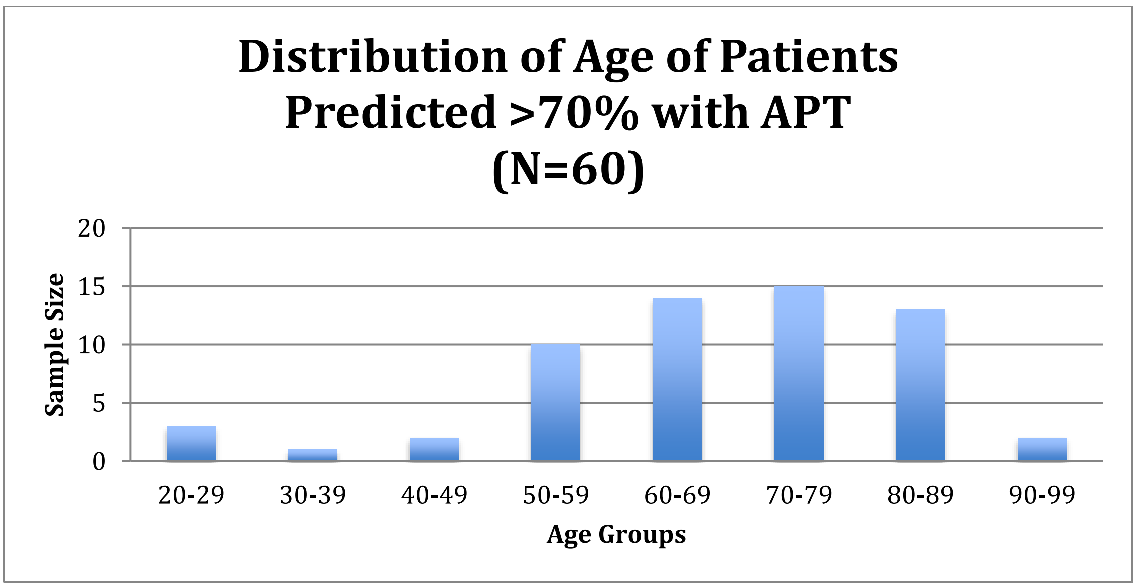
Table 2: Distribution of APT v.3 screening predictions

APT Prediction	Number Predicted (N=281) and Percent
0-19%	83 (30%)
20-39%	88 (31%)
40-59%	45 (16%)
60-69%	14 (5%)
≥70%	51 (18%) *41 also predicted with V.2*

A total of 60 patients were predicted for admission at 70% or greater by at least one version of the APT and included in this study. Of these, 41 were predicted with both versions, while the remaining 19 were predicted with only one version of the APT. Nine were predicted for admission only by APT v.2 and 10 were solely predicted by APT v.3. Additional data were collected on the 60 included patients. These data included the APT score, age, chief complaint, significant event timestamps, admission team, and other information recorded in Appendix 3.

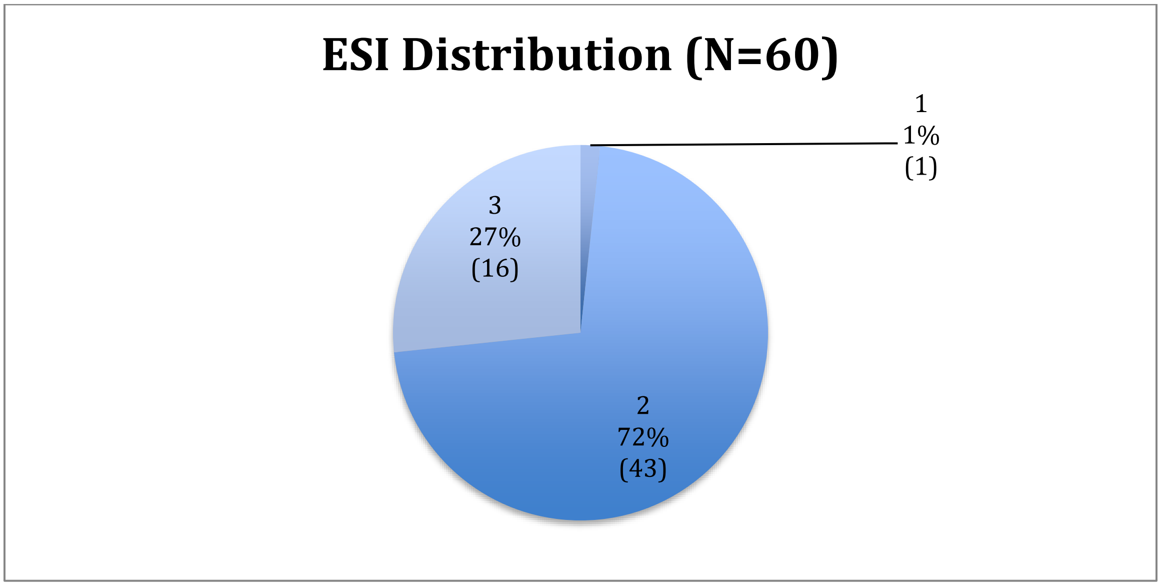
Description of Study Sample

Figure 1: Distribution of study sample age



The mean age of the 60 patients included in the study was 67.6 and the median age was 69.5. Figure 1 includes a bar graph of the ages of the study sample. Of these 60 patients, 27 were female and 33 were male. No patients with ESI level 4 or 5 were predicted for admission and included. Only patients with ESI level 1, 2, and 3 were predicted for admission. This includes one patient who was level 1, 43 who where level 2, and 16 who where level 3. Figure 2 displays the distribution of the ESI levels.

Figure 2: Distribution of Study Sample ESI Categories



Among patients predicted for admission, the most common chief complaint was shortness of breath (N=12), and chest pain (N=7) and weakness (N=6) where the second and third most common chief complaints, respectively. Of the patients admitted the most common admitting service was the MED team (N=8) that manages patients in the Observation Unit.

Description of the APT in Practice

Of the 60 patients predicted for admission a total of 48 were actually admitted. Their sex, age, presenting chief complaint, ESI level, APT scores, admitting diagnoses, and admitting team are provided in appendix 7. Several participants had high APT scores up to and including 100%, but those scores were based on small samples (<10). If the prediction was based on a small sample size then the patient did not undergo the BeRT process because of concerns regarding the reliability of the prediction.

The admitting diagnoses and the presenting chief complaints were similar for many of the 60 patients. The admitting diagnoses often were the exact same as the presenting chief complaint. For instance, participant 116 presented with hemoptysis (a cough that produces blood) and was admitted with the exact same diagnoses. For other participants the admitting diagnosis could reasonably be inferred from the chief complaint. Participants 104 and 125 both had chief complaints of leg swelling and their admitting diagnosis was deep vein thrombosis or DVT (blood clot in the leg).

Appendix 8 includes the sex, age, chief complain, ESI level, APT score, final diagnoses, and miscellaneous information for those patients who were predicted for admission but not admitted. Participant 205 eloped from the ED prior to his evaluation being completed so it is possible he could have been recommended for admission. Participant 210 who was ill with active cancer and complications from it was seriously considered for admission but was not ultimately admitted after shared decision making with him, his family, his oncology team, and the ED team. Participant 203 was evaluated by the Family Medicine team for admission but ultimately discharged.

The APT scores of the patients who were admitted and those that were not admitted were similar. Both groups were primarily in the 70s-80s%. The average APT score for patients who were admitted was 78% and the average APT score for those not admitted was 75%. The admitted patients tended have a higher probability for admission based on APT v.2 than APT v.3 with 27 (56%) having a higher prediction based on APT v.2. The opposite was true for patient not actually admitted. Of those not admitted 7 (58%) had a higher APT v.3 score.

One notable difference that can be found between these groups was the triage category. The group that was actually admitted had a lower rate of triage 3 level patients compared to the group that was not admitted. The admission group includes ten level 3 patients out of 48 (21%). The group that did not get admitted had six out of 12 (50%) patients in ESI level 3. Figures 3 and 4 display the distribution of the ESI level of these two groups.

Figure 3: Distribution of ESI level for patient actually admitted

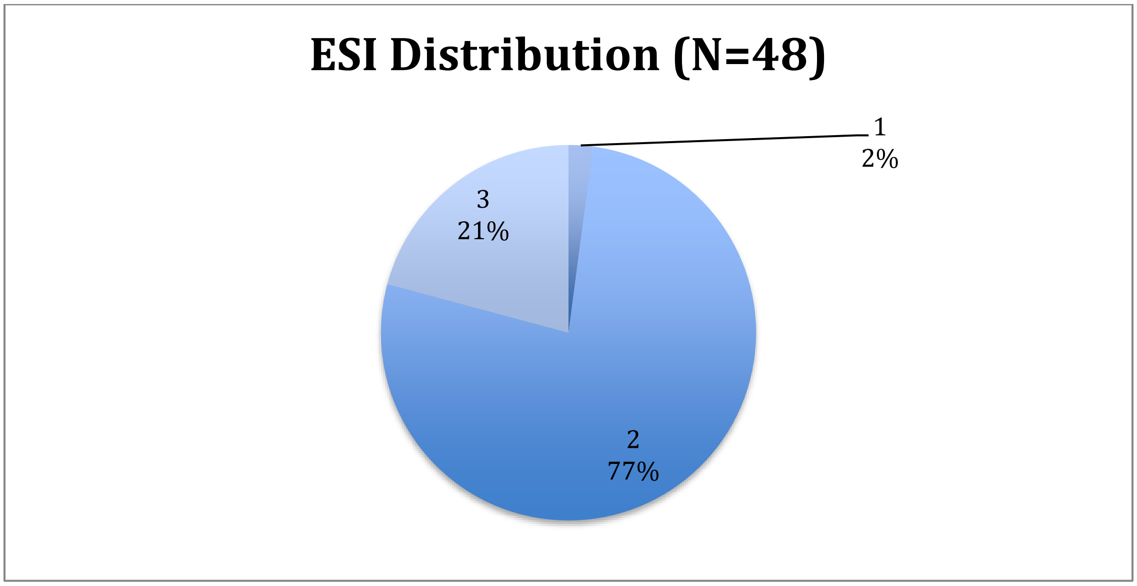
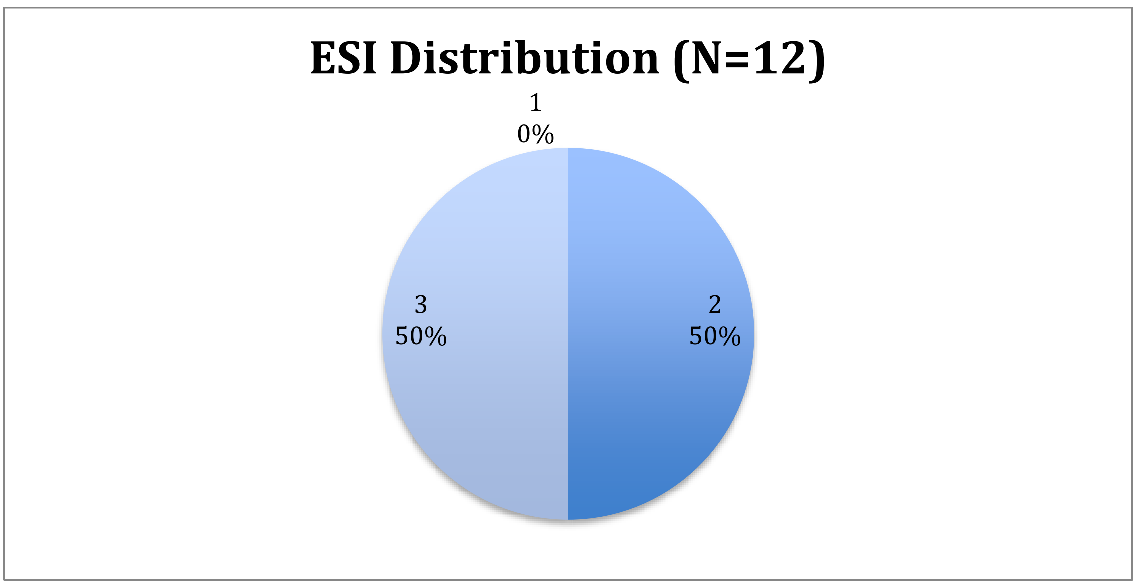


Figure 4: Distribution of ESI level for patient not admitted



Description and Comparison of APT v.2 and v.3 in Patients with APT Score 70% or Greater

The sample size each version of the APT uses as a basis to make a prediction is different. APT v.2 is based on 1 year of data while APT v.3 is based on 4 years of data. Also, the chief complaints of APT v.3 are more inclusive leading to less use of the category "other" to describe the chief complaint. APT v.2 uses 69 chief complaints including a category "other" and APT v.3 uses 385. Due to these differences, some patients were predicted for admission with one version of the APT but not the other. Of the 60 patients included in this study as having being predicted for admission 41 were predicted at 70% or greater by both versions of the APT. The remaining 19 were predicted by only one version of the APT. There were 50 patients with an APT v.2 score of 70% or greater and 51 patients with and APT v.3 score of 70% or greater. Using an APT threshold of 70 % as a minimum for inclusion resulted in higher actual admission rates than 70%. The APT v.2 prediction resulted in an actual admission rate of 78% (figure 3), and APT v.3 resulted in an actual admission rate of 82% (figure 4).

Figure 5: Actual admission rates based on an APT v.2 threshold of 70% or greater

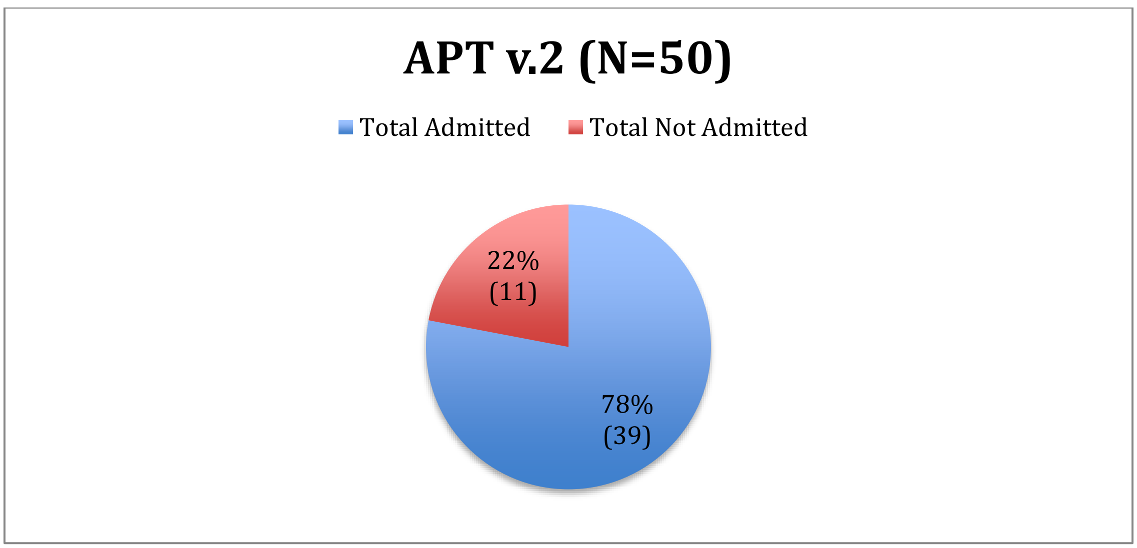
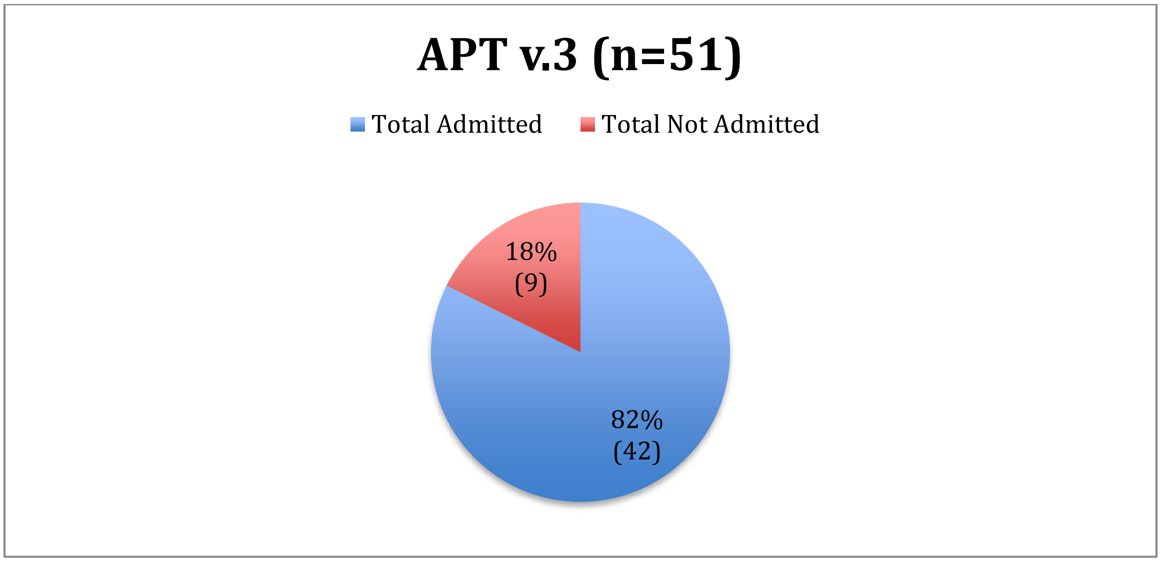


Figure 6: Actual admission rates based on an APT v.3 threshold of 70% or greater



Both versions of the APT identified both floor and ICU admissions. The percent of patients identified for admission who were admitted to the ICU was slightly higher in the APT v.2 group. The APT v.2 flagged patients had a 21% rate of ICU admission whereas the APT v.3 group had a 17% rate of ICU admission.

With regards to my ability to identify potential medical admissions based on triage data, using both APTs there were several patients who did not get admitted to a medical service. This was more common with APT v.3. This was 14% of the patients for APT v.3 and 5% of the patients for APT v.2. The table 3 surmises this information.

Table 3: Actual medical versus non–medical admissions

70% Threshold	Meeting APT v.2	Meeting APT v.3
Total Admitted	39	42
Medical Admit	37	36
Non-Medical Admit	2	6

Description and Comparison APT v.2 and v.3 in of Patients with a Score of 85% or Greater

APT v.2 identified more patients as having a score 85% or greater than APT v.3. A total of 24 patients were identified using APT v.2 and 14 with APT v.3. As with the 70% threshold, using an 85% score as a minimum for inclusion resulted in higher actual admission rates, albeit to a lesser extent. For APT v.2 87% of the patients were admitted and for APT 86% of the patients were admitted. See figures 7 and 8

Figure 7: Actual admission rates based on an APT v.2 threshold of 85% or greater

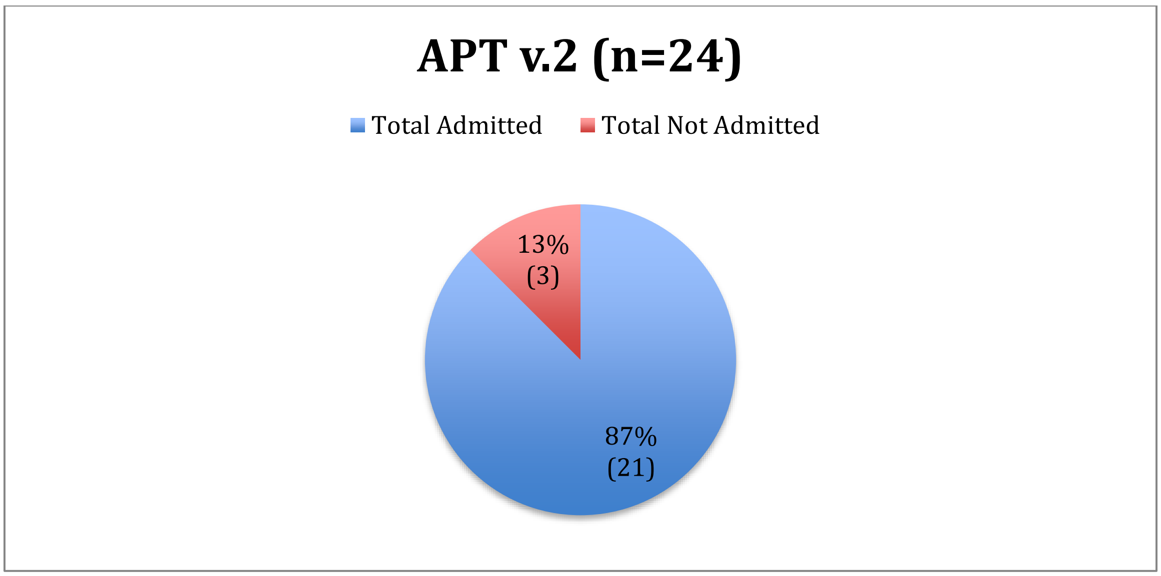
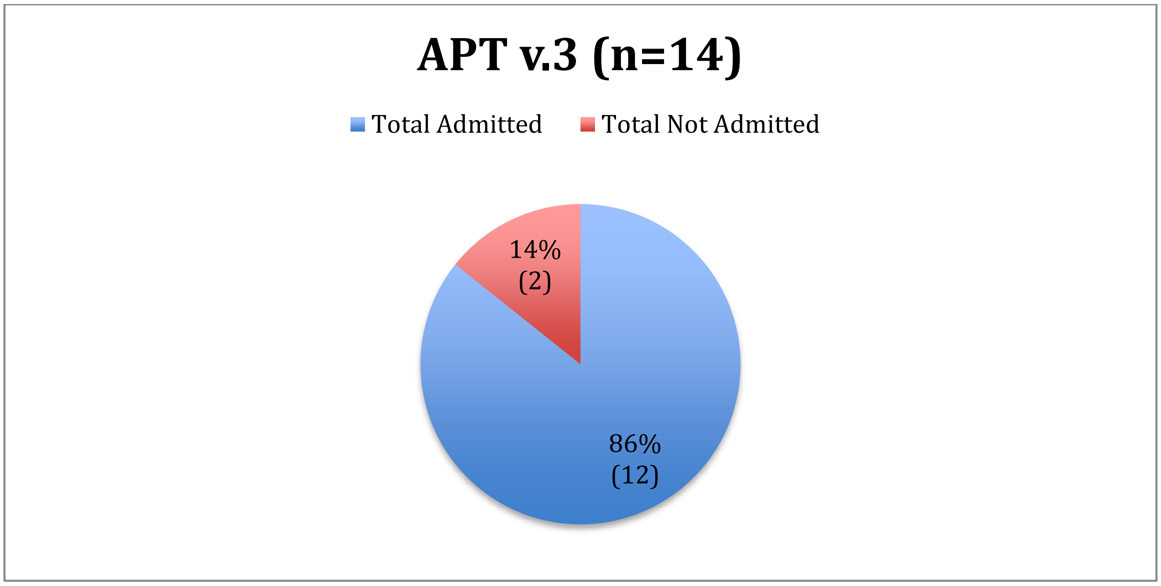


Figure 8: Actual admission rates based on an APT v.3 threshold of 85% or greater



With regards to the percentage of ICU admissions, using the threshold of 85% both versions of the APT had a higher rate of ICU admissions than at the 70% threshold. Using APT v.2 24 % of the predicted admissions went to the ICU and with APT v.3 25% went to the ICU.

My ability to identify medical admission based on triage data was greater using the 85% threshold than 70%. The total numbers of patients was smaller but with APT v.2 only 2 patients were not admitted to a medical service and with the APT v.3 version, all patients were admitted to a medical service. See the Table 4.

Table 4: Actual medical versus non–medical admissions

85% Threshold	Meeting APT v.2	Meeting APT v.3
Total Admitted	21	12
Medical Admit	19	12
Non Medical Admit	2	0

The BeRT Process

The sole patient to undergo a modified BeRT was a 67-year-old male with a chief complaint of chest pain and an ESI category of 2. This patient had an APT v.2 score of 86% and an APT v.3 score of 75%. He presented to the ED at 12:37. The MAO agreed that he would likely be admitted and most importantly, because he had a Left Ventricle Assistive Device (LVAD), he could only be assigned to the cardiology heart failure (MDD) team. He was identified by the APT at 13:04 but the patient did not get an actually bed request until 14:01 because the inpatient team came to evaluate the patient at 13:34 and wanted to place the order themselves. His inpatient bed was assigned at 18:20, and then he was changed to a different in patient bed at 20:40. He did not end up leaving the ED until 21:39 for a total ED length of stay of 9 hours 2 minutes or 542 minutes. His boarding time after bed request was 7 hours 31 minutes or 459 minutes. This compares to an overall mean boarding time of 371 minutes for all medicine services this day but shorter than the mean boarding time for the MDD service itself that same day of 526 minutes.

Aggregate Prediction Use of APT

In consultation with my doctoral committee, I added an aggregate prediction of ED admissions calculation starting on November 9, 2017. On 15 separate occasions between November 8 and December 15 I calculated an APT v.3 score on all patients in the ED with a medical complaint who had not yet had a disposition decision (admit or discharged). I then calculated an aggregate prediction admission score for these patients by multiplying the average admission probability for patients by the total number of patients. The number reflected the expected number of patients who would likely be admitted. I shared this information with the MAO and the ED attending physician responsible for patient movement, in order to help them judge the capacity of the ED and the hospitals ability to accept transfers from outside facilities.

This information was combined with other data available to the MAO and physician including bed availability and expected transfers to the hospital.

I present an example of the aggregate prediction ED admission score here. At 1500 on December 7 the ED had a census of 73 patients with 20 patients that had been identified by the ED providers as needing admission and were awaiting inpatient beds. The NEDOCS score was 200. This is the validated measure of ED overcrowding with a maximum score of 200. The hospital had 1 available Medical ICU bed, 1 available Medical Step down bed, and no available Medical floor beds. The APT predicted that another 6.29 patients currently in process in the ED would also require admission. This information reinforced the hospital's decision to remain of ED to ED transfer diversion given that the ED overcrowding was expected to worsen based on the aggregate prediction I provided.

User Experience with the Aggregate Prediction

I was not able to collect qualitative data about the experience with the BeRT process as planned, because there was only one patient who underwent the BeRT process. However, I did collect qualitative data from eight ED attending physicians and two MAOs regarding the aggregate prediction use of the APT. These qualitative data were analyzed and grouped into two themes.

<u>Qualitative Data Theme 1: Use of the APT as a Tool to Control Patient Flow</u>

The lead MAO in particular felt there was value in aggregate prediction use of the APT. She said of the tool and its aggregate prediction use, "This is where your tool could be really useful. I could see it being used as part of the PLC (Patient Logistics Center) in bed planning." She felt that "predicting the bed needs of the hospital 3-4 hours ahead of time could allow for the ED to throttle its transfers better instead of using the all or nothing diversion we use now." The MAOs universally saw value in the use of an aggregate prediction use of the APT.

Some of the junior attending physicians echoed this as well. One said, "As a new attending, having the most information I can about our capacity is really helpful." Another said she would like to see this predictive tool integrated into the EHR. The same attending thought it could be useful to have the score displayed in the EHR and there be an agreed upon threshold for the ED to stop accepting transfers from outside hospitals. The current method for this is for the attending to call the administrator on call from the hospital and obtain permission to stop accepting transfers.

Qualitative Data Theme 2: Using the Aggregate APT would Not be Helpful

Converse to the opinions of the previous theme, some attending physicians were not as enthusiastic having and aggregate prediction of patients expected to be admitted. One attending in particular, with > 25 years experience, expressed hesitancy to use the tool in this way saying, "I just accept everyone (transfers) and figure that we can just sort it out later." He felt that the ED and the hospital where in a state of constant capacity strain and that one tool would not make any significant improvement to a system that was so strained. Another attending, with about 10 years experience expressed some concern that the aggregate use of the APT would not capture the complexity of the ED in order to be useful.

CHAPTER 4 DISCUSSION

Through this project, I added to the evidence about the use of the APT on actual patients in the ED, including the practical aspects of APT implementation. While previous studies have addressed prediction of admission for possible future use (Barak-Corren, Fine, & Reis, 2017; Barak-Corren, Israelit, & Reis, 2017; Bradman et al., 2014; Stover-Baker, Stahlman, & Pollack, 2012; Vaghasiya, Murphy, O'Flynn, & Shetty, 2014), none of these studies sought to make use of this prediction for actual operations. In this project I translated evidence into practice by acting on this prediction through an early bed request process and subsequently by an aggregate prediction of future inpatient bed needs.

The purpose of this study was to improve the throughput of the ED by investigating the feasibility of using the APT at triage to identify patients likely to be admitted to expedite ED throughput through the use of a BeRT process. The goals were to positively impact patient flow and to lay the groundwork for future implementation of APT and BeRT process.

I was only able to directly improve throughput for the one patient who underwent the BeRT process. This patient had an approximately 30 minute shorter ED stay than other patients admitted to the same service that particular day. However, by using the aggregate prediction of admission I was further able to impact the throughput of patients by reinforcing the hospitals decision to remain on diversion during times of ED overcrowding thereby allowing the hospital to focus on throughput of patients currently in the ED.

Academic EDs tend to have more difficulty processing admitted patients (Horwitz, Green, Fau-Bradley, & Bradley, 2010). Patients at academic centers tend to be more complex, which is reflected in a scoring system developed by CMS. To address the varying complexity of patients address different hospitals, CMS (n.d.) calculates a score called the Case Mix Index (CMI) in order to normalize the different outcomes of patient care that occurs between different hospitals. Although the CMI is designed to address payment, the variation of different CMI scores could be used to understand the higher levels of complex processes that occur within academic centers. The study sites' CMI is the second highest in the local area and only lower than another local academic medical center. See appendix 9 for local CMI data. The complicated admitting process at the study site proved to greatly limit this project's goal of impacting patient flow. Yet the study was able to meet its goal of laying the groundwork for future implementation plans.

What was Learned about Using the APT to Inform an Early Bed Request Process

Only one of the 60 patients predicted for admission actually underwent the BeRT process. Even for this patient it was a modified BeRT process. Three patients were excluded from the BeRT process because even though they had a high APT score, their admission prediction was based on a small number of patients and the MAO and I did not feel confident in using the APT to initiate the BeRT process. For example, a 75-year-old female with a cough had an APT v.2 score of 100%. However, this prediction was based on only a total of 3 patients. The smaller patient samples were all predictions made using APT v.2.

Another sever patients were excluded from the BeRT process who had a high enough APT score but there was uncertainty about the level of care the patient would require. At the time of the APT calculation for these patients, the MAO was concerned that the patient may or may not require an ICU bed, thus making an early bed request not feasible without the knowledge of whether the patient would need a floor bed or an ICU bed. An example of this is a patient who had an APT v.3 score of 93% based on an ESI category of 2, an age of 57, and a chief complaint of hypotension. The patient did not undergo the BeRT process because it was felt that her blood pressure was so low that she could require advanced medical care only available in the ICU. However, after fluid resuscitation in the ED, she stabilized and was admitted to a floor bed on the Oncology (MDE) service.

Beyond what level of care a patient may or may not need, uncertainty about which admission team would care for the patient resulted in other patients not undergoing the BeRT process. At UNCH the various medical teams are regionalized, and in order to place a bed request the patient must have a known team. Regionalization is locating all the patients of a particular service in a particular area. For example, in order to be assigned to a 4th floor bed a patient must be either on a pulmonary service or an infectious disease service. On six separate occasions patients had a chief complaint of chest pain (or angina) and had an APT v.2 score of 86%. Because the results of testing performed in the ED helps guide the medicine team assignment, five of these patients did not undergo the BeRT process. Testing may include cardiac enzymes that help to determine if a patient has had a myocardial infarction or not. By convention, at the study site patients with a confirmed heart problem are admitted to the cardiology team whereas patients who have a suspected but not confirmed heart problem are admitted to another medical team. In the end, two of these patients were discharged from the ED; two where assigned to the medicine observations unit, one was admitted to the cardiology team, and the final one was the patient who did undergo the BeRT process.

Strengths of the Study and BeRT Process

The major strength of this project and the implementation of the BeRT process was the presence and buy-in of the MAO team. They proved to advocates for advancing the idea of the BeRT process. The lead MAO was paramount in gaining the willingness of the internal medicine and family medicine teams to trial the BeRT process based on the APT prediction. The lead MAO was also instrumental in developing the idea of using the APT to make aggregate predictions and the ways in which this aggregate prediction could be applied.

A second strength of the study was its use of quality improvement framework as opposed to a research framework. This allowed use of PDSA cycles and continuous improvement on a rapid cycle compared to the more stringent framework required from research. When the BeRT process did not prove successful based on initial methods those methods could be modified. This change would not have been possible if using a research framework but is quite acceptable under the guises of a quality improvement project demonstrating the value of the DNP approach.

Variability of Predictions Between APT v.2 and v.3

Another strength of the study was that it was the first study to evaluate the APT v.3. A previous study investigated the APT v.2 (Ring, 2017). I was able to compare the two versions of the APT. I found that for some patients the two versions of the APT had wide variability in the prediction. Though similar in design, APT v.2 predictions are based on 69 chief complaints and one year of data to make a prediction whereas APT v.3 used 385 chief complaints and four years of data.

Due to the limited number of chief complaints (N=69) available in APT v.2 some patients' chief complaints were grouped differently than with the APT v.3. If a chief complaint was not one of the 69 included in APT v.2, then the category "other" was selected for the patient instead. An example is a patient who presented to the ED with a chief complaint of "failure to thrive." The patient was made an ESI level 3 and was 75 years old. Using the APT v.3 that includes "failure to thrive" as a chief complaint, the patient's probability of admission was 70%. This prediction was based on a sample size of 33. APT v.2 does not contain "failure to thrive" as a chief complaint so the patient was predicted as having a 50% probability of admission using the "other" chief complaint. The category "other" is a large sample and contained 2,896 patients.

In some cases use of the "other" chief complaint in APT v.2 resulted in higher probability of admission. For example, one patient who was 81 years old male with an ESI level 2 and had a chief complaint of rash. The patient's likelihood of admission was 82% by APT v.2 with a chief complaint of "other," whereas using APT v.3 the chief complaint of "rash" yielded and admission prediction of 60%. The patient's rash was actually a skin and soft tissue infection called cellulitis, and the patient was actively being treated for cancer.

Table 5 displays the seven participants who had a 20% or greater difference in predictions between the two versions of the APT.

Table 5: Study participants with a 20% or greater difference in APT v.2 and v.3 predictions

Chief Complaint	**Age**	**ESI**	**APT v.2**	**APT v.3**	**Reason for Variation**
Possible Sepsis	72	2	100%	75%	Small sample in v.2. "Other" in v.3.
Cough	75	2	100%	80%	Small sample in v.2.
Facial Droop	86	2	100%	53%	Both sample pools small.
Leg Swelling	82	2	0%	92%	Both sample pools small.
Failure to Thrive	75	3	50%	70%	Use of "other" in v.2
Rash	81	2	82%	60%	Use of "other" in v.3.
Tachycardia	57	2	100%	66%	Small sample v.2

Barriers to the Implementation of the BeRT Process

The study has found several barriers to this process. They are complexity of the admissions process at the study site, limitation of the APT to differentiate level of care, limitation of the APT to identify a medical admission, and lastly institutional cultural barriers. However, though innovation potential other uses of the APT were found.

While the presence of the MAO and the buy-in of the MAO team were thought to be strengths of the study but the complexity behind the admissions process proved to be a large barrier. The patients at the study site are placed in inpatient beds regionalized to the service they are admitted to. Each of the thirteen different medical teams has a different nursing unit it prefers to admit patients to and a secondary back up unit. This means in order to place a bed request the patient must be assigned to a particular team. However, which team to patient would be assigned to is subject to numerous cofounders. Many of the teams that are teaching services on which residents care for patients are subject to caps on the number of patients they can admit in a day and on a shift. They are also subject to a cap on the number of patients on the service. Even if the APT predicted a patient for admission they could only be assigned to teams that had openings. When initially limiting patients to the MDA and the MDU service this was a barrier encountered.

Even when all medical teams were included in the study there were still problems with differentiating between the different teams. There are norms in place that limit the flexibility of which team may admit any given patient. Whether or not a patient would be admitted to the cardiology (MDC) service or not was a common question. As discussed previously, MDC at this institution admits patients with a positive common blood test called a troponin that signals heart damage. At other intuitions, other teams may admit patients with this positive test. If a patient where predicted likely to be admitted the question would remain if they would go to the MDC service or another team because the results of the troponin test were pending. This was particularly true for patients with chief complaints of chest pain and shortness of breath. These two chief complaints combined accounted for 21 of the 60 patients included in this study. This is not an insurmountable barrier. There is no definitive rule that requires admission to MDC for patients with a positive cardiac enzyme but rather it is by convention. If a patient were to be admitted to another service a cardiologist could still be consulted and evaluate the patient.

An additional level of complexity within the admissions process is that a different team, MDI, cares for patients in the medical ICU. As a result if a patient was highly likely to be admitted a BeRT process could not be started unless it was clear if the patient was going to the ICU or the floor. This would still be an issue even if it were not a different team because the beds are located in different nursing units. During this study it was felt by the MAO and myself that patient's with higher APT predictions tended to have a reasonable likelihood of being admitted to the ICU. Part of this would depend upon the patient's response to treatment in the ED. If a patient improved with interventions in the ED they may still need to be admitted but it would be to a floor bed as opposed to an ICU bed.

In addition to the problems with differentiating teams and levels of care there was a problem differentiating whether the patient would be admitted to a medical service or not. Similar to the regionalization that occurs with the medicine services, the surgery services house their patients in separate units. Abdominal pain is an excellent example of a chief complaint included in the APT that may result in a diagnosis requiring admission to either medicine or surgery. In this study this only accounted for one patient but potentially could be a more frequently encountered problem. Seemingly medical chief complaints such as hypotension and tachycardia did also result in surgical admissions.

Solutions to Implementing BeRT Process

The BeRT process through use of the APT could still be useful. This could be done either through refinement of the APT or use of the process at a different institution.

In its current state the APT and BeRT could be used at an institution that is large enough to have issues with overcrowding in the ED yet not as complex as the study site. If an institution does not use regionalization or have multiple services that are siloes then the institution could use this process. Some hospitals use only a hospitalist service that admits all medical patients to all inpatient beds. These are usually not academic medical centers. They are more likely to be community hospitals. In such a setting it would not matter if the patient had a positive cardiac enzyme or not because the same team would be caring for the patient.

Refinement of the APT would be required to address the issues of level of care and the problems with differentiating a medical versus a nonmedical admission. Perhaps including information such a comorbidities or recent admissions information would be helpful. Knowing that a patient has recently had surgery increases the likelihood of the patient being admitted to a surgical service regardless of the chief complaint. The APT could also be reformatted in its current state to include information on ICU admissions in addition to hospital admissions. Because it uses probabilities based on historical data, it would be just as feasible to use the combination of chief complaint, age, and triage category to calculate a probably of being admitted to the ICU.

Additional Lessons Learned about the APT

Both versions of the APT certainly have the power to predict admission. Their use could still be considered for use on individual patients or for aggregate use. Lessons learned during the implementation of this project could potentially be used to improve the tool, if deemed feasible by the development team. The first and foremost is that the APT does not take into account comorbidities. Work done by another graduate student has shown that inclusion of comorbidities may strength the APT (Ring, 2018). In this study, the one patient who underwent the BeRT process had a significant comorbidity of having severe heart failure requiring a left ventricular assistive device. The second is that an ideal APT would be able to have the capabilities to interpret free text. Both these issues can be seen in the patient mentioned above who had a chief complaint of rash but varying prediction between the two versions of the APT. While APT v.2 resulted in an 82% prediction of admission based on his age, chief complaint, and ESI category, APT v.3 only resulted in a 60% prediction of admission. Likely if another version of the APT would have include the patient's comorbidity of active cancer the prediction would have been higher as immune compromised individuals generally are admitted at a higher rate than those who are not immune compromised. This is especially true when an infection is involved.

This patient's "rash" was actually an infection of the skin and soft tissues called cellulitis with associated pustules (pus-filled bumps on the skin). If the APT were able to read text it would have recognized that the patient had cellulitis that was included in the triage free text. Instead the APT, in its current form, is limited by the triage nurses' choice of chief complaint, even if there were a more precise way to describe the chief complaint as the triage nurse was able to do in the free text of his or her note. The tool can only be as good as the data input into it. Making sure this input data is as accurate, thorough, and precise as possible is important to the use of the tool.

Variability between triage nurses of what is entered both in terms of chief complaint and ESI level will ultimately impact the APT prediction and its usefulness. If a triage nurse takes time to find the most accurate description of the patient's condition the prediction will be more closely based similar past patients. This comparison to past patients is how APT functions. The same is true for ESI category. Perhaps even more importantly, consistency of ESI level assignment will help ensure a more accurate prediction.

Reliance on the triage nurse to help make the APT more powerful seemed to be displayed in the differences between those who were actually admitted with a positive APT screening versus those who were not admitted. The portion of the APT that relies on human judgm ent of acuity is the ESI level. The group of patients who were not ultimately admitted had a much higher proportion of ESI level 3, 50% versus 21% in the admitted group. This is consistent with the design of the APT. ESI and age were both included in the APT because they were believed to be well correlated with likelihood of admission. It may be that if the triage nurse does not believe the patient is as sick then the patient is less ill and will not as likely require a hospital stay. This finding is supported in the ESI triage literature, which has demonstrated that patients assigned to more acute ESI levels (ESI level 1 or 2) have a higher likelihood of admission (Wuerz et al., 2001 & Eitel, Travers, Rosenau, Gilboy, & Wuerz, 2003). The APT takes this into account but perhaps a greater proportion of the probability needs to take this judgment into account. The literature does point to nurses having a reasonable ability to predict admission (Vaghasiya et al., 2014). Work done by another doctoral student is also showing that nurses can reasonable predict admission (Ring, 2018).

New Aggregate Use of the APT

Using the APT for aggregate patient predictions appears to be a promising use for the tool. It was not included in the original methods for the project but through PDSA cycles this use proved to be promising.

In this project the APT was used to make aggregate predictions of admissions for patients in the ED. This information could be integrated into the EHR and provide continuously updated information on the future inpatient bed needs. Aggregate prediction improves the power of the prediction. We were able to include confidence intervals with the aggregate prediction. This provides even more information useful to decision makers.

Such decisions makers could be the patient logistic center, the bed control center, house supervisor, ED administrator, or hospital administrator. During this study, the MAOs in particular expressed interest in this use of the APT. Again, the two surveyed both believed this use could be used to improve not only ED throughput but hospital throughput as well. This information could be used to predict the bed needs of the hospital hours before the patients are flagged for admission. It could be used to throttle the number of transfers being accepted either into the hospital or into the ED.

Limitations

The major limitation of this study was that it was implemented just by one person and just over a limited amount of time as a trial project. It is possible that with more time and patient interactions there would have been more patients who underwent the BeRT process. It is also possible that with more experience, the BeRT process could have been more ingrained within the organization.

This study also looked at only a limited patient population. Patients who where not expected to be admitted to medicine where not included in this study. Patients with surgical complaints where not screened using the APT. Pediatric patients were also not included.

This study also only took place at one institution. The APT and BeRT process have the potential to be successful at another institution. This hypothesis needs to be tested.

Future Work

<u>APT and BeRT Process</u>

The APT and BeRT process should be tested in another setting. Based on this study, the next site would ideally be a facility with a high enough volume that cause crowding and delays for admitted patients, yet has as a simple enough admission process that does not result in the complex decisions that guide the admissions at this study site. I believe that a large community hospital that deals with ED overcrowding but admits the majority of their patients to a single hospitalist service would benefit from using the APT and BeRT process.

APT Improvements

The APT can potentially be improved by including comorbidities. The APT does an excellent job in calculating based on the three current parameters but I suspect adding a fourth parameter of significant comorbidities could be used to strengthen its prediction without making it significantly more cumbersome to use. Active cancer would likely be the most significant of them. I recommend that the APT v.3 (not APT v.2) be used in future work, given that it is based on a large sample and the current chief complaints used in a common EHR. I also suggest that the APT also generate a probability of ICU admission.

Aggregate Predictions Using the APT

The potential application of using the APT to make aggregate predictions is the most novel result of this study. The next step towards translation of this tool will be to present and gain buy in from hospital wide stakeholders again, namely the Patient Logistics Center (PLC). This group is looking for predictive data it can use to make better decisions regarding patient flow. ED crowding tools that are currently in use, such as NEDOCS and EDWIN, are used to quantify and predict general ED overcrowding but have limited use in highly complex systems (Ahalt et al., 2016). The aggregate admission prediction tool developed here can be used to quantify future ED crowding as well, as it relates to admitted patients. The PLC, as the central location for patient movement, can use the aggregate APT to forecast whether or not the ED is going to be overcrowded with admitted patients. This will support operational decisions that can impact patient flow hours ahead of time.

I suggest that as a next step, the PLC leadership should be engaged along with hospital administration to perform a full-scale trial implementation of the aggregate APT to evaluate its utility in gauging when to place the hospital on ED-to-ED transfer diversion. The current method is based on the subjective opinion of the house supervisor and ED attending physician, all of who have varied tolerances to overcrowding. I envision a set threshold whereby if the number of patients boarding and aggregate prediction total a predesigned number of patient this triggers automatic diversion. This would help standardize decisions about when to go on diversion.

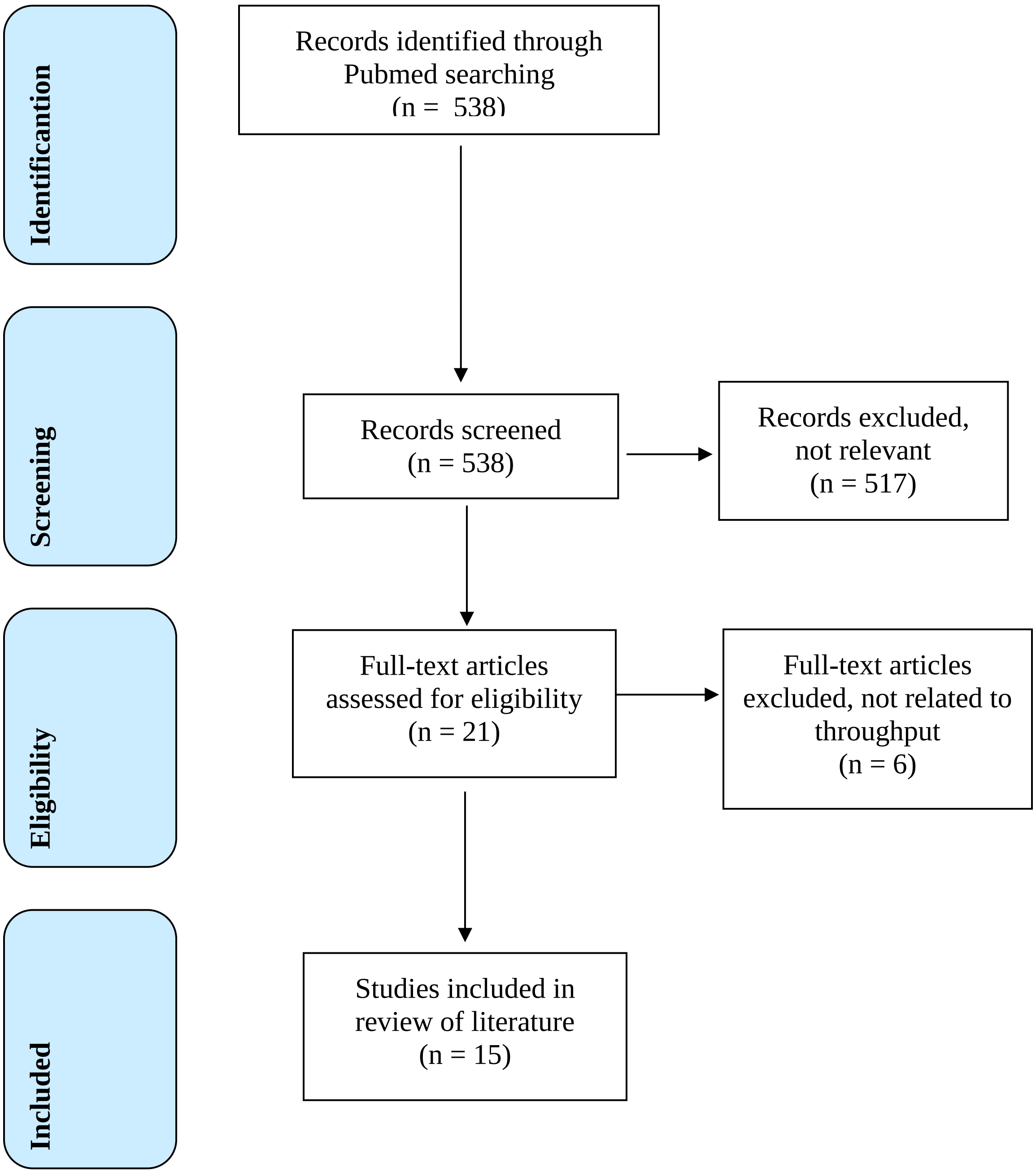
CHAPTER 5: CONCLUSIONS

In this project I was not able to meet the goal of impacting patient throughput directly by use of the APT and BeRT process. The admission system proved to be even more complex than initially understood. However, I was able to add to the collective evidence regarding the practicality of using the APT and BeRT process. This does meet my goal of laying the groundwork for future implementation. Lessons learned from this pilot implementation can be carried forward to future projects.

I was able to explore the use of the latest version of the APT. This project was the first time APT v.3 has ever been used and it performed well with easier use given the more complete chief complaints included. Through real world experience with the APT, I have been able to make suggestions for future ways to improve the tool.

Ultimately, through a quality improvement approach, I was able to develop a novel way of using the APT. The aggregate use of the APT has the potential to provide a previously unthought-of way to predict in patient bed needs hours ahead of time. Further, it could be useful for guiding operation of the whole department and hospital in that the tool can be used to predict overcrowding of the admissions process.

APPENDIX 1: PRISMA 2009 FLOW DIAGRAM



APPENDIX 2: STUDY SITE ED CORE MEASURES

ED Core Measures:

Data from 1/1/2015 - 12/31/2015

Measure (all reported in minutes):	UNC	Rex	WakeMed	Duke	DRH	Alamance	NC Avg - Very High	National Avg - Very High
Median LOS -Overall for Admitted Patients	432	357	372	417	393	272	340	346
Boarding Time for Admitted Patients	237	236	146	148	190	95	131	137
Median LOS - Overall for Discharged patients	234	194	185	283	172	185	172	172
Door to Doc time	30	35	40	33	42	61	38	30
LWBS	4%	3%	2%	7%	6%	4%	2%	2%

(Medicare, 2017).

APPENDIX 3: INFORMATION TABLE OF DATA GATHERED FOR PATIENTS ENROLLED IN STUDY

Date	Time	Day	Visit ID	Study ID	Age	Sex	CC1	CC2	CC3	ESI	APT	BeRT Time	Bed Asgn	Team	Diagnosis	Depart ED	Misc Info

APPENDIX 4: QUALITATIVE INFORMATION REGARDING IMPLEMENTATION

1. For patients identified for early admission, did the bed request after triage (BeRT) process seem to expedite their admission?

2. For patients not identified for early admission, did their admission process or ED stay seem to be affected?

3. Where there any unexpected ramifications of the BeRT process?

4. Do you have suggestions for changing the identification or processing of patient who may benefit from the BeRT process? How could the process be better?

5. Did the process seem to change your workload?

6. Do you think patients perceived any differences in their care if they underwent the BeRT process?

APPENDIX 5: HYPOTHETICAL PRESENTATION OF AGGREGATE APT SCORE

Patient ID	APT Score	95% Confidence Intervals for individual patients			
301	0.32	0.22	0.68		
302	0.7	0.21	0.3		
303	0.45	0.25	0.55		
304	0.22	0.17	0.78		
305	0.1	0.09	0.9		
306	0.81	0.15	0.19		
307	0.32	0.22	0.68		
308	0.69	0.21	0.31		
309	0.11	0.2	0.89		
310	0.08	0.07	0.92		
Total # of Patients	Average Admissions Prediction	Expected Admissions		95% Confidence Intervals of Prediction	
10	0.38	3.8		1.3	6.3

APPENDIX 6: QUALITATIVE INFORMATION REGARDING THE AGGREGATE PREDICTION APT SCORE

1. Does the report make sense to you?
2. Do you think this report captures the complexity of the patients in the ED today or the likely patients who will be admitted today?
3. Do you find this report helpful?
4. How do you plan to use this information today?
5. How else could you imagine this information being used?

APPENDIX 7: PATIENTS CORRECTLY PREDICTED FOR ADMISSION

(N=48)

Study ID	Sex	Age	CC	ESI	APT v.2	APT v.3	Diagnosis	Team
101	F	72	Possible Sepsis	2	100%	80%	Sepsis	MDI
102	M	84	Altered Mental Status	2	88%	81%	Altered Mental Status	FAM
103	M	84	Weakness	3	70%	72%	Urinary Tract Infection	FAM
104	M	50	Leg Swelling	2	NA	75%	DVT	MDH
105	F	78	Hypotension	2	83%	82%	Shock, Sepsis, Elevated Troponin	MDI
106	F	65	Weakness	2	87%	88%	Sepsis secondary to pneumonia	MDB
107	F	70	Weakness	2	87%	86%	LVAD patient	MDC
108	F	52	Abdominal Pain	2	60%	74%	AMS. Possible SBP	MDW
109	M	58	Evaluation of abnormal EKG	2	66%	71%	Afib with rvr	SRS
110	F	69	Altered Mental Status	2	88%	85%	Brain Metastases	MDE
111	M	78	Shortness of Breath	2	89%	88%	A. fib with rvr. Sepsis	MDI
112	F	57	Hypotension	2	79%	93%	Hypotension	MDE
113	M	67	Chest Pain	2	86%	75%	Syncope and Dyspnea on Excerption	MDD
114	F	74	Weakness	3	70%	72%	Numbness	Neurology
115	F	63	Shortness of Breath	2	87%	88%	Acute Blood Loss Anemia	MDI
116	F	54	Hemoptysis	3	70%	44%	Hemoptysis	MDB
117	F	75	Cough	2	100%	80%	Abd Pain. Cough. AKI on CKD	FAM
118	M	67	Chest Pain	2	86%	75%	Chest Pain	MED
119	F	76	Cardiac Arrest	1		100%	Expired in the ED	MDC
120	M	86	Facial Droop	2	100%	53%	Ischemic Stroke	Neurology
121	M	88	Elevated Blood Sugars	2	82%	76%	GI Bleed with anemia	MDW
122	F	26	Shortness of Breath	2	69%	77%	Tracheobronchitis	MDG
123	M	74	Hypotension	2	83%	82%	Hypotension	MED

Study ID	Sex	Age	CC	ESI	APT v.2	APT v.3	Diagnosis	Team
124	M	81	Altered Mental Status	3	76%	72%	Hyperkalemia	MED
125	M	82	Leg Swelling	2	0%	92%	DVT	MDA
126	F	76	Weakness	2	70%	72%	Acute Pancreatitis	MED
127	M	80	Chest Pain	3	83%	66%	Chest Pain	MED
128	M	92	Shortness of Breath	3	84%	79%	Atrial Flutter	MDC
129	M	43	Shortness of Breath	2	81%	82%	Ingestion of Toxic Substance, Metabolic acidosis	MDI
130	F	75	Failure to thrive	3	50%	70%	NSTEMI	MDC
131	M	95	Altered Mental Status	2	89%	82%	AMS secondary to Respiratory Failure	MDI
132	M	89	GI Bleeding	2	90%	98%	SVT. GI Bleed.	MDW
133	M	56	Hypotension	2	79%	93%	Gastric Artery Bleed	SRH
134	M	61	Shortness of Breath	3	71%	68%	COPD Exacerbation	MED
135	M	81	Rash	2	82%	60%	Pustular Rash, Malignant Neoplasm	MDE
136	M	29	Shortness of Breath	2	69%	77%	CF Exacerbation	MDG
137	F	61	Elevated Blood Sugar, symptomatic	2	76%	83%	Diabetes	MDE
138	F	86	Chest Pain	2	82%	74%	Chest Pain	MED
139	M	60	Blood in Stool	2	100%	83%	Melena	MDB
140	F	75	Shortness of Breath	2	89%	89%	Community Acquired Pneumonia	MDA
141	M	69	Fever between 9 weeks and 74 years	2	96%	90%	NVD	MDE
142	M	86	Abdominal Pain	2	85%	82%	Abdominal Pain	MDU
143	M	63	Shortness of Breath	3	72%	68%	Afib, AKI, COPD	CICU
144	M	61	Shortness of Breath	2	87%	88%	Sub massive PE	MDI
145	F	79	Chest Pain	2	86%	79%	Afib with rvr	MDC
146	F	45	GI Bleeding	3	37%	75%	Hemtachezia	SRG

Study ID	Sex	Age	CC	ESI	APT v.2	APT v.3	Diagnosis	Team
147	M	57	Tachycardia	2	100%	66%	A Flutter	SRE
148	F	84	Angina	2	86%	74%	Atypical CP	MED
Total higher prediction per version=					27	20	Equal with both version=	1

APPENDIX 8: PATIENTS PREDICTED FOR ADMISSION BUT NOT ADMITTED

(N=12)

Study ID	Sex	Age	CC	ESI	APT v.2	APT v.3	Diagnosis	Misc
201	F	59	Chest Pain	2	86%	75%	A. Fib	Discharged to facility
202	M	58	Chest Pain	2	86%	75%	Conversion Disorder	Discharged
203	M	57	Fever	3	70%	72%	Nausea, vomiting, Leukocytosis	Discharged by family medicine
204	F	70	Abdominal Pain	2	75%	80%	Abdominal Pain. Constipation	Discharged
205	M	71	Weakness	3	70%	72%		Patient eloped
206	F	84	Edema	3	67%	76%	Swelling	Discharged
207	M	60	Shortness of Breath	3	71%	68%	Dyspnea	Discharged
208	F	63	Altered Mental Status	3	70%	72%	Hepatic Encephalopathy	Discharged
209	M	29	Fever	2	73%	76%	Cough. SOB	Discharged
210	M	74	Shortness of Breath	2	89%	89%	Hydrothorax	Discharged. Oncology Patient.
211	F	65	Shortness of Breath	3	71%	68%	Weakness	Discharged
212	F	34	Shortness of Breath	2	70%	76%	Anxiety, Dysphagia	Discharged
Total higher prediction per version=					4	7	Equal with both versions=	1

APPENDIX 9: CASE MIX INDEX (CMI) OF LOCAL HOSPITALS

Hospital	**Total CMI**
Duke	2.4483
UNC Chapel Hill	2.1468
Rex	2.0094
Wake Med	1.9091
Duke Regional	1.6481
Alamance Regional	1.5386

(American Hospital Directory, n.d.)

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